Journal of Agricultural and Resource Economics 33(2):212–231

Spatial Dependence in Hedonic Property Models: Do Different Corrections for Spatial Dependence Result in Economically Significant Differences in Estimated Implicit Prices?

Julie M. Mueller and John B. Loomis

While data used in hedonic property models are inherently spatial in nature, to date the majority of past regression analyses have used OLS models that overlook possible spatial dependence in the data when estimating implicit prices for environmental hazards. This paper explicitly addresses spatial dependence in a hedonic property model. We use robust testing procedures to determine the existence and type of spatial dependence in our OLS Model. After identifying the nature of the spatial dependence, OLS estimates of the implicit price of wildfire risk are compared to implicit prices obtained using a spatial error model with three different spatial weighting matrices. Spatially corrected estimates of implicit prices are found to be nearly the same as those obtained using OLS. Our results indicate that the inefficiency of OLS in the presence of spatially correlated errors may not always be economically significant, suggesting nonspatial hedonic property models may provide results useful for policy analysis, and spatial and nonspatial hedonic property models might be pooled in meta-analysis.

Key words: forest fires, hedonic property models, spatial econometrics

Introduction

Spatial issues are receiving increased attention in environmental and natural resource economics, including the use of spatial hedonic property models to value environmental amenities and disamenities (Bateman, Yang, and Boxall, 2007). In the first stage of hedonic property models, the estimated value of an environmental amenity is the marginal effect of the amenity on the observed house price. Hedonic property models also can be used to estimate the demand for an environmental amenity, and hence the nonmarginal willingness to pay for that amenity. Ordinary least squares (OLS) has been the common empirical method for estimating the hedonic price function.

Julie M. Mueller is assistant professor, W. A. Franke College of Business, Northern Arizona University; John. B. Loomis is professor, Department of Agricultural and Resource Economics, Colorado State University. Craig Bond, Patty Champ, and David Mushinski provided valuable insight and feedback on several versions of this manuscript. We thank Justin Butteris for his help with ArcGIS and Craig Bond for providing the MATLAB software. We are very grateful to Nate Peterson, our GIS specialist, for his contributions to this project. Peter Boxall and Phil Watson also offered comments and suggestions on early versions. Donald Lacombe provided useful assistance with MATLAB code. Comments from two anonymous reviewers greatly contributed to this paper. Any remaining errors are solely the responsibility of the authors. Funding for this research was provided by the USDA Forest Service and Colorado State University under Agricultural Experiment Station Regional Research Project No. W2133.

Review coordinated by Douglas M. Larson.

Many previous hedonic studies have used distance-based measures to the amenity or natural hazard to control for spatial effects, but did not statistically test for spatial dependence between house sales. In order to diagnose and correct for spatial dependence, a researcher needs calculations for distances between all housing parcels and relevant environmental data. Without the use of Geographical Information Systems (GIS) to analyze geo-coded parcel-level data, it is extremely time consuming to calculate the distances from each house to all neighboring houses in a data set. Because of recent advances in GIS, geo-coded data are becoming widely available in many locations, although such data often have limited availability outside the United States and Europe.

Spatial dependence can occur due to spatial correlation between the dependent variable (also known as a spatial lag process) and as a consequence of spatial correlation in the errors. Failure to correct for a spatial lag process when it exists results in biased coefficient estimates. Failure to correct for spatially correlated errors results in inefficient coefficient estimates. The data used in hedonic property models are spatial in nature because they are based on house sales in a given area. A common mantra in real estate pricing is "location, location, location." Thus the price of a house is strongly influenced by the price and quality of houses immediately surrounding it, the general neighborhood of houses, and its relative location to amenities (e.g., parks, beaches) and disamenities (e.g., landfills and other point-source pollutant sites).

While many past studies attempted to control for neighborhood effects with demographics of the Census tract, school quality, and proximity to amenities with distance, the influence of surrounding house prices was not explicitly modeled until recently. Given real estate appraisers' use of "comparable" sales in the immediate vicinity of a house being priced, one would expect a high correlation between the price of a house and nearby homes. In addition, it is reasonable to believe that some measurement error related to location could exist in the independent variables—i.e., even with thorough demographic data, a researcher can fail to measure some aspect of the data that is related to location. Hence, the spatial nature of hedonic property models has a depth beyond simple distances to environmental amenities and disamenities. Advances in spatial econometric techniques now allow analysts to test and correct for spatial dependence of both types discussed above.

Does OLS without spatial corrections give a reasonable empirical estimate of the value of an environmental amenity when spatial dependence is present? Of particular interest to analysts and policy makers is whether the difference in estimated implicit prices with and without corrections for spatial dependence is of economic significance. By economic significance, we are referring to differences in value estimates large enough to cause changes in decisions based upon those benefits. Do previous estimates of implicit prices from hedonic property models suffer from bias or inefficiency large enough to affect policy decisions because of a failure to correct for spatial dependence? If coefficient estimates are biased, policies may be based on incorrect point estimates. If coefficient estimates are inefficient, researchers may fail to reject policy-relevant null hypotheses when those hypotheses should be rejected. Many past hedonic property studies did not perform explicit spatial analyses. Consequently, are past meta-analyses of hedonic property studies still useful for benefits transfer? These are some of the questions we address with the empirical results from this study.

Literature Review

Several earlier studies have used hedonic property models to estimate the marginal implicit price for the risk of natural disasters such as floods (Chivers and Flores, 2002; Bin and Polasky, 2004), earthquakes (Beron, Murdoch, and Thayer, 1997), and wildfires (Loomis, 2004). For example, employing a hedonic model to estimate the effect of flooding on residential property values, Bin and Polasky (2004) report that houses located within a floodplain have lower prices than houses located outside a floodplain. Furthermore, the price differential was found to increase after a major hurricane caused severe flooding. Bin and Polasky conclude that recent flooding causes an increase in perceived risk of flooding. Their results suggest that after a natural disaster, increased risk perception causes a decrease in the value of houses located in high-risk areas.

Hedonic property models that consider spatial effects are becoming increasingly popular. Many different techniques for modeling spatial dependence exist. Several recent hedonic property studies note the difference between estimated coefficients using spatial error or spatial lag models versus OLS estimates. To date, however, few spatial hedonic property models have estimated the effects of a natural hazard. What follows is a brief summary of a sample of hedonic property studies that investigate natural hazards using methodologies similar to that presented here.

In a study on the effect of wildfire *risk* on house prices, Donovan, Champ, and Butry (2007) estimate four spatially corrected hedonic property models using maximum-likelihood techniques to investigate changes in the effects of wildfire risk variables on house prices after provision of fire risk information. They also consider changes in the effects of amenity variables directly related to wildfire risk after provision of wildfire risk information. After implementing likelihood-ratio tests for both spatial lag and spatially correlated errors, they use a general spatial model that accounts for both a spatial lag process and spatial autocorrelation in the errors. In their study, accounting for spatial dependence is highly statistically significant—i.e., both ρ and λ are statistically significant in the general spatial model. The authors report large differences in estimated coefficients ranging from 37% to 167% relative to OLS. Therefore, the bias resulting from failure to test and properly account for spatial dependence in their hedonic property model would be both statistically and economically significant, and would likely result in incorrect policy implications.

Additional evidence for the importance of spatial effects in hedonic studies is presented in Brasington and Hite's (2005) analysis of the effects of air, water, and soil contamination. In a first- and second-stage hedonic property model, influence of the environmental hazard is determined by estimating distance to the nearest point-specific pollution site. For both the first and second stages of the hedonic analysis, they use a spatial Durbin model that includes spatially lagged dependent and independent variables. The spatial lag parameter is statistically significant in both stages, and the authors find relatively large differences in estimates of the implicit price of environmental quality for the OLS model relative to the spatial Durbin model. Although their study does not measure a natural hazard, such as wildfires, Brasington and Hite's analysis does measure the hedonic price of distance to an environmental disamenity. It is interesting to note, however, that their spatial models do have economically significant differences relative to OLS estimations. Brasington and Hite conclude that researchers should at least test for spatial effects in hedonic models.

Hunt et al. (2005) present a similar warning in the conclusion of their analysis on the impact of logging on the hedonic price of remote fishing trips in Alberta, Canada. Their hedonic model is not a hedonic property model, as the dependent variable in this case is the price of remote fishing trips. Yet, the estimation is an attempt to measure the value of another environmental disamenity—logging. Their independent variable of interest is the amount of logging occurring within 3 km of the lake where the fishing trip occurs. Thus, they use a distance cutoff similar to our two-mile cutoff, and examine the change in willingness to pay for a fishing trip due to increases in logging. In fact, the impacts of logging can be quite similar to the impacts of recent wildfires in terms of how they change people's views. Hunt et al. use robust testing to select between a spatial autoregressive model and a spatial lag model, and determine that a spatial lag is necessary. Including a spatial lag in this hedonic model caused most of the OLS parameter estimates to deflate. Because the OLS estimates were significantly different than the estimates from the spatial lag model, they conclude that researchers should exercise considerable caution when using OLS to estimate econometric models with inherently spatial data.

In a paper estimating values for ecosystem services and comparing spatial estimates to OLS estimates, Pattanayak and Butry (2005) note that failure to account for a spatial lag process and spatial autocorrelation leads to an underestimation of benefits. The authors estimate demand for ecosystem services and compute estimates of increases in welfare from the services provided by watershed management using spatial lag, spatial error, and combined spatial lag and error models. Spatial models generate welfare estimates 1.25–1.33 times greater than OLS estimates. The welfare estimates are moderately greater for the spatial models, and Pattanayak and Butry argue that the benefits of watershed management could be undervalued without the use of spatial econometrics.

Thus, several papers using methodologies similar to ours report a range of large to moderate differences in estimated costs of environmental hazards or benefits of environmental amenities. Yet, Kim, Phipps, and Anselin (2003) find little difference in a hedonic estimation of willingness to pay per household for improvement in air quality for OLS estimates relative to spatially corrected estimates. They employ a spatial hedonic model to estimate the marginal benefits of improvements in sulfur dioxide and nitrogen dioxide concentrations. Using robust tests, they observe indication of a spatial lag process. Like Pattanayak and Butry (2005), Kim, Phipps, and Anselin find the spatial parameters to be highly statistically significant. However, OLS only slightly changes the estimates of marginal benefits.

To date, little consistency is found among studies to indicate when estimated implicit prices for spatial hedonic models, using either a spatial lag or spatial error model, differ greatly from OLS implicit prices. Studies that explicitly include distance measures (e.g., Brasington and Hite, 2005; Hunt et al., 2005) still may have significant differences in estimates of spatially corrected models. In contrast, studies that do not include distance (such as Kim, Phipps, and Anselin, 2003) report small differences in OLS estimates versus spatial lag and spatial error models.

A primary objective of this paper is to extend the literature on spatial dependence by comparing estimated coefficients for spatial models to OLS estimates to determine if spatial corrections result in large differences in the estimated effects of wildfires on house prices. We follow a rigorous testing procedure to inform our spatial model choice.

We also examine differences in spatial effects on marginal implicit prices using three different weighting matrices to inspect the robustness of our results. The insights gained from this study may be valuable to analysts wanting to use previous hedonic studies for benefits transfer and policy making.

Empirical Model Specification

Hedonic property models infer values of environmental amenities or hazards based on observed housing purchase decisions are considered revealed preference methods of nonmarket valuation. Rosen (1974) first proposed the detailed theoretical construct for this model. It is based on the proposition that identical houses in similar neighborhoods will have different prices if the houses have different levels of an environmental amenity. Homebuyers are willing to pay more for a house with an environmental amenity such as a waterfront location. The resulting house price differential between houses with varying levels of an amenity is homebuyers' marginal willingness to pay for that amenity. Consequently, in order to determine the marginal implicit price of an environmental amenity using a hedonic property model, it is necessary to control for other characteristics that determine house price, such as structural characteristics, neighborhood demographics, and housing market trends. [See Taylor (2003) and Palmquist (1991) for a comprehensive discussion of the theoretical aspects of hedonic property models.]

In our hedonic property model, the dependent variable is the natural log of the real sale price, adjusted using the housing price index for Los Angeles, Riverside, and Orange counties (1983 base year). A log-linear specification allows the marginal effect of each independent variable to vary with the level of the dependent variable. Thus, the marginal effects of independent variables change as house price varies. Little theoretical guidance exists on the choice of functional form for hedonic property models because the predicted hedonic price is the result of the behavior of many different buyers and sellers (Taylor, 2003). It is unlikely that a hedonic price function would be linear because this assumes the marginal effect of an independent variable is constant for all houses regardless of differences in house price (Freeman, 1993).

Cropper, Deck, and McConnell (1988) investigated the issue of functional form in hedonic property models by performing simulations. They found that linear Box-Cox transformations result in the best estimates of implicit prices. However, they also found evidence that in the presence of unobserved attributes or when some housing attributes are replaced by proxy variables, then simpler functional forms, including the semi-log, provide better estimates of implicit prices. In addition, other methods with more flexible functional forms are not readily implemented in the presence of spatial dependence (Kim, Phipps, and Anselin, 2003). Although several alternative specifications are possible, we chose the log-linear specification because it is commonly found in the literature. (Further analysis of the functional form specification in the OLS model is available from the authors upon request.)

To address the temporal effects of wildfires on house prices, a sale date for each house is required. The recorded sale date is not the date when the actual purchase decision was made because offers on house purchases are made one to two months prior to the recorded sale date. Since homebuyers are locked into their contracts once an offer is made, the time element of our model is represented by a decision date, defined as 60 days prior to the recorded sale date. For example, if a sale date is April 30, 1998, the decision date is March 1, 1998.[1]

The independent variables of interest are wildfire indicator variables. Controls for housing structure and neighborhood demographics are included. The general model is as follows:

$$P_{it} = f(E_{it}, S_i, N_i), \tag{1}$$

where P_{it} is sale amount at decision date t, with sale amount deflated using the annual housing price index for Los Angeles, Orange, and Riverside counties (1983 base year); E_{it} represents environmental variables of interest for house i at time t; S_i denotes structural characteristics of house i; and N_i is neighborhood demographics for house i.

The choice of included independent variables for our first-stage hedonic property model was based on prior research, data availability, and data characteristics (i.e., correlations). Including irrelevant variables in an OLS regression results in large standard errors for the coefficient estimates, increasing the probability of type II errors (failing to reject the null hypothesis when the null is false). Furthermore, including several highly collinear explanatory variables in a regression may result in unreliable parameter estimates. Failure to include relevant variables, however, results in biased coefficient estimates (Taylor, 2003).

Many of our environmental variables are also based on distance. The spatial error process as detailed below arises from data measurement issues. Spatially correlated errors can be a result of measurement error related to location, or some mismatch in the data related to space (Bell and Dalton, 2007). The extent to which distance-related variables are included as explanatory variables may affect the likelihood of spatially correlated errors occurring in the model because it increases the amount of information related to distance used to explain variation in the dependent variable. However, if the independent distance-related variables are incorrectly specified, spatial autocorrelation will remain a problem. We chose explicit distance cutoffs for our fire variables and also include a variable to indicate distance to U.S. Forest Service (USFS) land, both of which reduce the likelihood that we will find spatial dependence in the errors.

The following are the independent variables we chose to include in our empirical specification:

- Environmental and Location Variables, E_{it}:
  a. *After One Fire* is an indicator variable equal to one if a house sold after and is located within 1.75 miles of exactly one wildfire,
  b. *After Two Fires* is an indicator variable equal to one if a house sold after and is located within 1.75 miles of exactly two wildfires,[2,3]
  c. *Days Since Most Recent Fire* indicates number of days since the most recent wildfire,

[1] The timing adjustment is similar to the adjustment used by Loomis and Feldman (2003).

[2] We include dummy variables that are equal to one if the house sold after one fire and after two fires. Therefore, the estimated coefficients on the *After Fire* dummy variables are relative to those houses that sold before any of the fires.

[3] To make distinct the effects of a first and second fire, *After One Fire* is equal to one only for those houses that sold after and were located within 1.75 miles of exactly one fire. Similarly, the *After Two Fires* variable is equal to one only for those houses that sold after and were located within 1.75 miles of exactly two fires.

d. *Distance to USFS Land* represents distance to the edge of the nearest USFS-owned land (meters), and

e. *Elevation* is elevation of the house lot (meters) above sea level.

The elevation of a house lot serves as a proxy for vegetation type (higher elevations tend to have more flammable vegetation in southern California). Houses located at higher elevations and nearer to forests have a higher risk of burning from a wildfire.

- Housing Structure Variables, S_i:
  a. *Square Feet*,
  b. *Number of Bedrooms*,
  c. *Number of Bathrooms*, and
  d. *Year Built*.

Several measures of housing characteristics were available. Many of the housing characteristics are highly correlated. Table 1 shows correlations for relevant variables. *Square Feet* and *Number of Bathrooms* are highly correlated. When all structural characteristics are included, the model shows signs of collinearity problems. *Square Feet* is a commonly used explanatory variable in hedonic property models to control for size of housing structure, and therefore is the structural characteristic we decided to include. Because *Number of Bedrooms* is not statistically significant when included with *Square Feet*, it is dropped in the final specification. We also include *Year Built* as a measure of housing structure quality.

- Neighborhood Demographics Factors, N_i:
  a. *Median Household Income* is the median household income in the Census tract (year 2000 dollars), and
  b. *% With No High School Degree* indicates percentage of residents in the Census tract above 18 years of age with no high school degree.

Neighborhood characteristics commonly included in hedonic models are school district quality and household income (Taylor, 2003). A direct measure of school district quality is unavailable within our data, so a measure of the percentage with no high school degree in a neighborhood is used as a proxy for the relative level of educational attainment in a particular community. Neighborhoods with high percentages of educated people generally have higher quality schools. Median household income is also included as a proxy for neighborhood desirability.

General trends in real house prices may occur over time. To reflect these general market trends in the real house prices, we include a daily time trend variable (*Trend*). The empirical model specification is as follows:

$$\text{(2)} \quad \begin{aligned} \text{Log}(\textit{Real Sale Price}) = {} & \beta_0 + \beta_1 * \textit{After One Fire} + \beta_2 * \textit{After Two Fires} \\ & + \beta_3 * \textit{Days Since Most Recent Fire} + \beta_4 * \textit{Square Feet} + \beta_5 * \textit{Year Built} \\ & + \beta_6 * \textit{\% With No High School Degree} + \beta_7 * \textit{Median Household Income} \\ & + \beta_8 * \textit{Distance to USFS Land} + \beta_9 * \textit{Elevation} + \beta_{10} * \textit{Trend}. \end{aligned}$$

Table 1. Correlations for Relevant Variables

	After One Fire	After Two Fires	Days Since Most Recent Fire	No. of Bedrooms	No. of Bathrooms	Square Feet	% With No HS Degree	Median Household Income	Trend
After One Fire	1.00								
After Two Fires	–0.49	1.00							
Days Since Most Recent Fire	0.02	0.42	1.00						
Number of Bedrooms	–0.06	0.08	0.02	1.00					
Number of Bathrooms	–0.09	0.11	0.07	0.59	1.00				
Square Feet	–0.06	0.10	0.08	0.62	0.81	1.00			
% With No High School Degree	0.02	–0.07	–0.12	–0.32	–0.40	–0.41	1.00		
Median Household Income	–0.03	0.10	0.10	0.27	0.32	0.37	–0.62	1.00	
Trend	–0.07	0.76	0.51	0.01	0.07	0.06	–0.11	0.10	1.00

Spatial Models

Data that are inherently spatial in nature can exhibit two types of spatial dependence—spatial dependencies across observations of the dependent variable (spatial lag) and spatial dependence across error terms (spatial autocorrelation). If omitted variable bias related to the location of a house parcel exists, then the errors in a hedonic property model may exhibit spatial autocorrelation. In contrast, a spatial lag process is less likely to exist in a hedonic property model. A spatial lag process indicates that values of the dependent variable are related for reasons beyond sharing similar characteristics (Bell and Bockstael, 2000). Several options are available for estimating spatial models, including Bayesian estimation and general-method-of-moments techniques. However, maximum-likelihood (ML) estimation remains the most commonly applied technique in economics for spatial estimation and is the method of estimation employed in this paper.

If data exhibit a spatial lag process, a spatial autoregressive (SAR) model is appropriate. A SAR model uses ML techniques to estimate

$$y = \rho \mathbf{W} y + \mathbf{X}\boldsymbol{\beta} + \varepsilon, \tag{3}$$

where $\mathbf{W}$ is the $n \times n$ weighting matrix, $\boldsymbol{\beta}$ is a vector of estimated coefficients, $\varepsilon \sim N(0, \sigma)$, and ρ is the spatial lag operator.

Spatially correlated errors are likely to occur when measurement error is related to location (Anselin and Bera, 1998). In a hedonic property model, if some neighborhood effects are not captured in the demographic characteristics, OLS will result in spatially correlated errors. With y as the dependent variable and $\mathbf{X}$ as a matrix of independent variables, the spatial error model is of the form:

$$\begin{aligned} y &= \mathbf{X}\boldsymbol{\beta} + \mu, \\ \mu &= \lambda \mathbf{W}\mu + \varepsilon, \end{aligned} \tag{4}$$

where λ is a coefficient on the spatially correlated errors.

If both a spatial lag process and spatial autocorrelation are present, a general spatial model allows for a spatial lag and spatially correlated errors, constructed as:

$$\begin{aligned} y &= \rho \mathbf{W}_1 y + \mathbf{X}\boldsymbol{\beta} + \varepsilon, \\ \varepsilon &= \lambda \mathbf{W}_2 \varepsilon + \mu, \end{aligned} \tag{5}$$

where y, $\mathbf{X}$, $\boldsymbol{\beta}$, and ε are as defined above. $\mathbf{W}_1$ and $\mathbf{W}_2$ are weighting matrices corresponding to the spatial lag process and the spatial error process, respectively. $\mathbf{W}_1$ and $\mathbf{W}_2$ need to be different for proper identification of equation (5), unless the process is modeled as a spatial moving average (Anselin et al., 1996). The general spatial model, while useful conceptually, is rarely needed for proper specification (Anselin, 2005). After a series of tests, we determined that the proper model specification for our data is a spatial error model (SEM). Below, we proceed by comparing OLS estimates to SEM estimates.

Spatial Weights

Testing for spatial dependence and estimating spatially corrected models requires the use of a spatial weights matrix. The weights matrix essentially models the "neighbor" relationship within the observations of the dependent variables. Weights can be based on contiguity (e.g., borders) or on distance. The nature of our data dictates spatial weights based on distance because we do not have information on the borders and sizes of our parcels. Intuitively, each of our houses are considered a point in space. The weights matrix $\mathbf{W}$ essentially captures similarities between houses in a given neighborhood or geographical area which would be ignored using nonweighted OLS estimation techniques. $\mathbf{W}$ is an $n \times n$ weights matrix of the form:

$$\mathbf{W} = \begin{bmatrix} \omega_{11} & \dots & \dots & \omega_{1n} \\ \vdots & \omega_{22} & \dots & \vdots \\ \omega_{n1} & \dots & \dots & \omega_{nn} \end{bmatrix}.$$

Wherever there is a nonzero element in the weights matrix, two parcels are considered "neighbors." If observations i and j are not considered neighbors, $\omega_{ij} = 0$. Therefore, the spatial weights matrices are considered "sparse" matrices because they have relatively few nonzero elements. MATLAB was used to generate the spatial weights matrices.[4]

Weights based on distance define neighbors as all parcels within a minimum cutoff distance, or the k nearest neighbors to each given observation. The benefit of k-nearest-neighbors weighting matrices is that they eliminate the possibility of islands, or observations having no neighbors (Anselin and Bera, 1998). Boxall, Chan, and McMillan (2005) use an inverse-distance weights matrix with a cutoff of 4 km in their hedonic analysis of the impact of oil and natural gas facilities on house prices. Hunt et al. (2005)

[4] The MATLAB code used for generating the spatial weights matrices and the spatial models is found in the *Spatial Econometrics Toolbox* by James LeSage. The toolbox and all documentation are available for download at http://www.spatial-econometrics.com.

also employ a distance-based weights matrix in their spatial hedonic analysis, while Kim, Phipps, and Anselin (2003) use a nearest-neighbors type distance matrix.

There is very little formal evidence supporting choice of weighting matrices (Anselin, 2002). While the choice of the appropriate weighting matrix is determined by the researcher, it may also be influenced by the particulars of the data set. For example, spatial data sets modeling regions will often use weights generated by contiguity formulations as opposed to distance. In a spatial hedonic study comparing generalized-moments estimators to maximum-likelihood estimators, Bell and Bockstael (2000) found the estimated coefficients to be more sensitive to the choice of weighting matrix than the method of estimation. They used weighting matrices based on inverse distance and contiguity.

To ensure our estimates are robust to the choice of weighting matrix, we use three different spatial weights matrices for our estimations: four nearest neighbors, eight nearest neighbors, and an inverse-distance matrix. The four-nearest-neighbors weights matrices have nonzero elements for the specified number of nearest neighbors for each observation. Each weights matrix is then row-standardized whereby the elements of each row sum to one. This facilitates the interpretation of the spatial weights as the averaging of neighboring values. MATLAB finds the nearest neighbors for each observation by identifying those with the smallest Euclidean distance. The four-nearest-neighbors (4NN) weights matrix has four nonzero elements in each row for the four nearest neighbors for each observation. Similarly, the eight-nearest-neighbors (8NN) weighting matrix has eight nonzero elements in each row for the eight nearest neighbors for each observation. Therefore, in the 4NN weights matrix, $\omega_{ij} = 1/4$ for the four nearest neighbors of a given house, and zero otherwise; for the 8NN matrix, $\omega_{ij} = 1/8$ for the eight nearest neighbors of a given house, and zero otherwise.

If spatial dependence exists in our data, prices of houses clustered together are likely to be affected by wildfires in the same way, resulting in a loss of information. That is, prices of houses located farther away from each other should exhibit less spatial dependence. In order to capture this effect in the spatial model, we generated an inverse-distance weighting matrix. To facilitate estimation, a weighting matrix should be sparse.

For our distance matrix, we consider parcels "neighbors" if they are located within the minimum Euclidean distance such that every parcel has at least one neighbor. In contrast to the nearest-neighbors weighting matrices, the number of neighbors varies between parcels in this inverse-distance matrix. The nonzero elements of the inverse-distance matrix are the inverse of the Euclidean distance between two parcels for parcels located within the minimum distance requirement.

Let d_{ij} represent the Euclidean distance between observations i and j, and let b represent the minimum distance such that every parcel has at least one neighbor. This is a common distance chosen when constructing spatial weights matrices because it eliminates "islands" or houses without any neighbors. Then $\omega_{ij} = 1/d_{ij}$ if $d_{ij} < b$, and $\omega_{ij} = 0$ otherwise. Next, the weights are row-standardized so the sum of the weights in each row equals one. For example, parcels located in densely developed areas can have up to 112 neighbors in our data, while other parcels have only a few neighbors. This allows neighbors located closer to each other to have higher weights than neighbors located far away.

In many ways, the inverse-distance spatial weights matrix provides a more intuitive representation of neighborhood structure because it more accurately represents heterogeneity in the neighborhood structure. For instance, a house located in a densely populated area is likely to have many neighbors, and a house in an isolated location may have few or only one neighbor.[5] The inverse-distance weighting matrix has 151,658 nonzero elements, while the 8NN matrix has 14,048 and the 4NN matrix has only 7,024.

Row standardization of the weights matrix allows ease of computation. However, for the inverse-distance matrix, row standardization changes the interpretation of the spatial relationship. Row-standardizing the inverse-distance matrix rescales the weights. This rescaling does not change the interpretation of the weights in a nearest-neighbors matrix, but since each observation has different numbers of neighbors in an inverse-distance matrix, row standardization rescales the weights in each row differently. Therefore, it implicitly changes the weights of neighbors across observations (Bell and Bockstael, 2000).

Following the procedure suggested by Anselin (2005), we begin by estimating equation (2) using OLS. Next, we perform a series of Lagrange multiplier (LM) tests for both spatial lag dependence and spatial autocorrelation. LM tests offer desirable aspects not found in other tests such as the Moran's *I*-test (Anselin, 1988). LM tests are computed on the basis of the specification under the null, they provide indications of multiple types of misspecification, they have clear asymptotic properties, and robust LM tests have power even if two types of spatial dependence are present. First, we use simple Lagrange multiplier tests for spatially correlated errors and a spatial autoregressive process. Simple LM tests may fail to accurately determine the nature of spatial dependence (Anselin et al., 1996). Following Anselin et al., we perform robust LM error and robust LM lag tests. The results from the robust tests determine our model of choice, the spatial error model. We then examine the differences in estimated implicit prices for OLS versus the SEM.

While robust tests are used in our analysis to select the best spatial specification, we refrain from choosing between weighting matrices. Bayesian methods can be used to choose both the best model specification and the best weighting matrices. This is a useful extension for further research, and is an important area for expansion of the methodology of spatial estimation (Holloway, Lacombe, and Lesage, 2007). However, for the purposes of this paper, we compare maximum-likelihood estimates to OLS for all three weighting matrices. Our hypothesis is that in some cases, the difference between estimated marginal values may not be policy relevant, despite the presence of statistically significant spatial effects. The contribution of this study is an analysis of the difference in estimated coefficients between OLS and spatial error models, given the nature of our data and environmental hazard.

Data and Sampling Methodology

We obtained several data sets from various sources and merged them to form a database that includes housing parcel sale date, sale amount, location, demographic characteristics, and fire distances. Each housing parcel is a single-family residence located

[5] Row-standardizing eliminates the possibility of a noncontinuous parameter space. See Bell and Bockstael (2000) for a thorough discussion.

within 1.75 miles of a relevant wildfire. All parcels sold at least once between 1989 and 2003.[6]

Over 54,000 single-family residences were available for sampling. Outliers were removed from the sample if they were recorded as having less than 500 square feet, if the sale amount in dollars per square foot was less than $50, and if the sale amount appeared to be a data entry error.[7] In addition, houses with zero bedrooms or zero bathrooms were eliminated from the sample. Because we linked housing data with demographic data using a zip code, houses with no recorded zip code were eliminated from the sample. After outliers were removed, the sample was stratified by distance to wildfire and sale date. Each wildfire was mapped with a series of quarter-mile rings from the fire center, until the last ring, which is 1.75 miles from the fire center. A target of 25 houses for each distance stratum and each year was used. Houses were randomly sampled when there were more than 25 houses for a given distance and sale date.

Our 1.75-mile cutoff is consistent with the distance cutoffs used in previous hedonic literature on environmental hazards and disamenities. For example, Loomis (2004) measured the effect of a forest fire on house prices in a town located about two miles from the fire. Gayer, Hamilton, and Viscusi (2000) use quarter-mile distance cutoffs ranging from 0.25 mile to 1 mile in a hedonic study on Superfund sites. In another hedonic study on the impact of oil and natural gas facilities, Boxall, Chan, and McMillan (2005) found that oil and sour gas facilities located within 4 km (2.48 miles) significantly affect house prices. All of the fires modeled in our study are small fires (about 1,000 acres each), and none of them resulted in houses burning to the ground. From discussion with U.S. Forest Service fire specialists, the 1.75-mile cutoff chosen seemed reasonable based on fire risk and other concerns such as evacuation areas.[8]

Fire Sampling Methodology

Wildfires that occurred in the 1990s were chosen for analysis to ensure the availability of sufficient data after each wildfire to analyze long-term effects. Los Angeles County was selected because there were numerous wildfires within the wildland urban interface in the county during the 1990s. The study area is composed of five fires and is approximately 5.25 miles across. A map of the fire area is provided in figure 1. The darkest areas are the fire perimeters. The gray shaded areas represent 0.25-mile rings extended out from each fire perimeter. The tiny gray shapes represent housing parcels.

The Sylmar fire occurred on November 25, 1991, and the Polk fire occurred on November 28, 1991. Because the Sylmar and Polk fires occurred within three days of and just a few miles from each other, they are considered one fire (fire A) for purposes of this analysis. The Towseley fire occurred on December 4, 1995, and is treated as one fire (fire B). The Placerita fire occurred on July 3, 1997, and the Sierra fire on August 8, 1997. Because the Sierra fire occurred less than 40 days after the Placerita fire, also within just a few miles of the Placerita fire, the Placerita and Sierra fires are also counted as one fire (fire C). All three wildfires are of comparable size—fire A burned 937 acres, fire B burned 818 acres, and fire C burned 977 acres.

---

[6] We know only the most recent sale date of a house.

[7] For example, there were several observations with sale amounts of $0, $8, $27, or $99999999.

[8] No houses were lost to fire in our fire area.

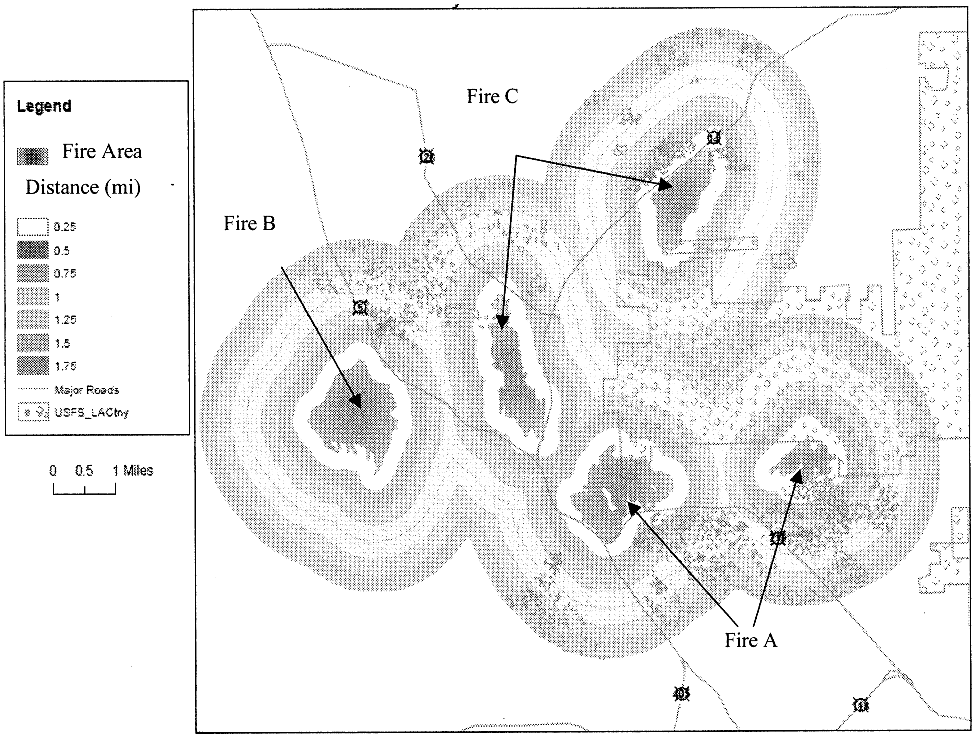

Figure 1. Map of fire area

Recall that we generated an *After One Fire*, *After Two Fires*, and *Days Since Most Recent Fire* variable for each house. Each house in the study area is located within 1.75 miles of at least one of the fires, but may have sold before the nearest fire. A house within our sample is considered to experience a wildfire if it sold after and was located within 1.75 miles of the wildfire[9]—i.e., the *After One Fire* variable is equal to one if a house sold after and was located within 1.75 miles of exactly one fire. Alternatively, houses that sold before all fires located within 1.75 miles of the house are coded with *After One Fire* equal to zero and are treated as a control group. Likewise, our *After Two Fires* variable is equal to one for those houses that sold after and were located within 1.75 miles of exactly two fires.[10]

Table 2 presents the number of houses in our data for each of the three wildfires. Fire A is a first wildfire for 1,181 houses. Fire B is a first wildfire for 657 houses and a second wildfire for 807 houses. All 807 of the houses with fire B as a second wildfire had fire A as a first wildfire. Fire C is not a first wildfire for any houses, but it is a second wildfire for 465 houses and a third wildfire for 34 houses. Because they sold before the nearest fires, 682 houses have *After One Fire*, *Days Since First Fire*, *After Two Fires*, and *Days Since Second Fire* equal to zero. By allowing different wildfires to be the "first" wildfire

[9] Effects on prices of houses located farther than 1.75 miles from fires are not analyzed here, and this may be an important avenue for future research. In OLS estimations, we tested the robustness of smaller cutoffs and found that the estimated coefficients on the environmental variables of interest were robust to different distance cutoffs.

[10] Only 34 houses experienced a third fire, so we do not analyze the effect of a third fire.

Table 2. Timing of Fires and House Sales Data

Fire	Year	Sample Inclusions for Each Fire	No. of Acres Burned
A	1991	1st fire for 1,181 houses	937
B	1995	1st fire for 657 houses 2nd fire for 807 houses	818
C	1997	1st fire for 0 houses 2nd fire for 465 houses 3rd fire for 34 houses	977
Total No. of Houses = 2,520			

Note: 682 houses sold before all fires within 1.75 miles.

for different houses, we reduce the likelihood that our estimates are biased by spurious correlation with other events.[11]

The parcel data were obtained from Los Angeles County through Nobel Systems.[12] The data contain the geographic location, sale date, sale price, and structural characteristics of housing parcels in Los Angeles County.[13] Sale price data are deflated using an annual Housing Price Index (HPI) for Los Angeles, Orange, and Riverside counties.[14] Annual unemployment rates for the state of California were obtained from the Bureau of Labor Statistics website.[15] Table 3 reports summary statistics for the variables included in the final empirical model. Because the HPI uses 1983 as a base year, the mean real sale amount for each fire area is in 1983 dollars. The demographic variables are from the 2000 Census, so median household income is measured in year 2000 dollars. Seventy-three percent of the houses sampled are located within 1.75 miles of and sold after at least one wildfire; 50% of the houses sampled are located within 1.75 miles of and sold after at least two wildfires.

Results

The OLS results are reported in table 4. The coefficients on *After One Fire* and *After Two Fires* are negative and statistically significant, indicating house prices drop after first and second wildfires. The estimated coefficient on *Days Since Most Recent Fire* is positive and statistically significant, showing house prices increase over time after the most recent wildfire. The estimated coefficients on *Square Feet* and *Year Built* are as expected, indicating relatively large and newly built houses have higher selling prices. The estimated coefficients on the demographic variables are also as expected, confirming that houses in relatively wealthy and educated communities have higher selling prices.

[11] The estimated implicit prices in the OLS model are robust to shorter distance specifications. Analysis using shorter distance cutoffs is available from the authors upon request.

[12] We thank Shil Niyogi of Nobel Systems for his assistance with the Los Angeles County parcel data.

[13] We do not have data on parcel size.

[14] The annual Housing Price Index was obtained from the Bureau of Labor Statistics website (http://data.bls.gov/cgi-bin/srgate) and typing in the series id CUURA421SAH.

[15] The website is http://data.bls.gov/cgi-bin/srgate, with the series id LAUST06000003.

Table 3. Summary Statistics for Variables Included in Final Empirical Model

Variable	Mean	Std. Error
Real Sale Amount (year 1983 $)	151,907	3,026
Log of Real Sale Price	11.85	0.24
After One Fire	0.73	0.01
After Two Fires	0.50	0.01
Days Since Most Recent Fire	422.77	29.40
Square Feet	1,842	36.70
Year Built	1974	0.35
% With No High School Degree	21.76	0.43
Median Household Income (year 2000 $1,000s)	65.68	1.31
Elevation (meters)	1,426	28.40

Table 4. OLS Results (dependent variable = *Log of Real Sale Price*)

Variable	Coefficient	t-Statistic	t-Probability
Constant	5.960961	5.65	< 0.00001
After One Fire	−0.197238	−9.94	< 0.00001
After Two Fires	−0.128919	−5.19	< 0.00001
Days Since Most Recent Fire	0.000039	3.44	< 0.00001
Square Feet	0.000310	28.56	< 0.00001
Year Built	0.003058	5.51	< 0.00001
% With No High School Degree	−0.006215	−9.53	< 0.00001
Median Household Income	0.000001	1.52	0.13
Elevation (meters)	−0.000410	−9.34	< 0.00001
Trend	0.000019	2.62	0.01
$R^2 = 0.60$			
$\bar{R}^2 = 0.60$			
No. of Observations = 1,762			

Our results also reveal that houses at high elevations, ceteris paribus, have a lower selling price. This may be due to the increased fire risk for houses located at higher elevations. Despite being deflated using the HPI, house prices show a slowly increasing trend in our sample.

For our initial tests for spatial dependence, we perform simple LM tests for spatially correlated residuals and a spatially lagged dependent variable.[16] The null hypothesis of the LM spatial error test is of no spatial correlation in the residuals. With all three weighting matrices, we strongly reject the null hypothesis of no spatial correlation in the residuals.[17] For the simple LM spatial lag test, we reject only the null hypothesis of

[16] Donald LaCombe provided the MATLAB code for these tests—it is readily available from the authors upon request.

[17] The p-values for the test using each weighting matrix are < 0.0001.

no spatial autocorrelation using the inverse-distance weighting matrix.[18] Thus, the simple LM tests show evidence for both spatially correlated errors and a spatially lagged dependent variable, and robust testing is necessary.

Following the steps suggested by Anselin (2005), we perform robust LM spatial error tests using all three weighting matrices. In all cases, the null hypothesis of no spatial autocorrelation in the errors is strongly rejected.[19] Because the robust tests are only appropriate when the null hypothesis is rejected in the simple tests, we perform the robust LM spatial lag test using only the inverse-distance weighting matrix. The robust LM spatial lag test has a p-value of 0.38 using the inverse-distance matrix. Although the simple LM test indicated we should reject the null hypothesis of no spatial lag, the robust test failed to reject the null hypothesis of no spatial lag using the inverse-distance weighting matrix.

Our series of tests led to the conclusion that the spatial error model is the appropriate model to fit our data. The results from the SEM are reported in table 5. The estimated coefficients on *After One Fire* and *After Two Fires* are negative and statistically significant in every specification, indicating house prices drop following a first fire, and then drop again following a second fire. The estimated coefficients on the housing structure, demographic, and trend variables have similar signs and significance as under OLS. Thus, we focus our attention on the marginal implicit prices from OLS and the SEM.

When calculating the implicit price for the fire variables in our semi-log specification, we multiply the estimated coefficient times the mean house price, i.e.:

$$\text{(6)} \qquad \textit{Marginal Implicit Price} = \hat{\beta} * \bar{y},$$

where $\hat{\beta}$ represents the estimated coefficient on the *After Fire* variable, and $\bar{y}$ is the average house price (\$165,015). Table 6 shows the estimated implicit prices from the different models. The first fire results in a price drop ranging from \$29,802 to \$32,547, and the second fire produces a price drop ranging from \$16,161 to \$21,274. The cumulative price drop after two fires ranges from \$46,419 to \$53,821. Table 7 reports the percentage difference in the SEM implicit prices relative to OLS. The largest difference in estimated coefficients occurs when using the inverse-distance matrix, where a 24% difference is found in the estimated implicit prices. Note that in every case, OLS overestimates the implicit price drop. Specifically, the absolute value of the estimated drop in house price is larger with OLS than with the spatially corrected models, but the range of errors is from approximately 5% with the 4NN weighting matrix to 24% with the inverse-distance weighting matrix.

It is also important to note any differences in the standard error estimates of the coefficients. For the coefficients of interest, i.e., the *After Fire* and *Days Since Most Recent Fire* variables, the standard errors in the OLS model versus the SEM model are essentially unchanged.[20] Therefore, we can conclude that correcting for spatial dependence resulted in little difference in both coefficient estimates and the standard errors of the coefficient estimates.

---

[18] The p-values for the test using the 4NN and 8NN weighting matrices are 0.24, while the p-value for the test using the inverse-distance weighting matrix is < 0.0001.

[19] The p-values for the test are < 0.0001 for the nearest-neighbors weighting matrices, and 0.01 for the inverse-distance weighting matrix.

[20] We thank an anonymous reviewer for pointing this out. Detailed comparisons of the standard errors are available from the authors upon request.

Table 5. Spatial Error Model Results (dependent variable = *Log of Real Sale Price*)

	SEM with 4NN		SEM with 8NN		SEM with Inverse Distance	
Variable	Coefficient	*z*-Prob.	Coefficient	*z*-Prob.	Coefficient	*z*-Prob.
Constant	5.663640	< 0.00001	5.434914	< 0.00001	4.048589	< 0.00001
After One Fire	–0.185894	< 0.00001	–0.180601	< 0.00001	–0.183369	< 0.00001
After Two Fires	–0.121638	< 0.00001	–0.117202	< 0.00001	–0.097934	< 0.00001
Days Since Most Recent Fire	0.000036	< 0.00001	0.000035	< 0.00001	0.000045	0.0001
Square Feet	0.000311	< 0.00001	0.000312	< 0.00001	0.000302	< 0.00001
Year Built	0.003177	< 0.00001	0.003275	< 0.00001	0.003969	< 0.00001
% With No High School Degree	–0.006196	< 0.00001	–0.006125	< 0.00001	–0.006561	< 0.00001
Median Household Income	0.000001	< 0.00001	0.000000	< 0.00001	0.000000	0.0016
Elevation (meters)	–0.000369	< 0.00001	–0.000345	< 0.00001	–0.000294	< 0.00001
Trend	0.000018	0.01	0.000018	0.01	0.000012	0.0909
Spatial Error Parameter, λ	**0.177985**	**< 0.00001**	**0.285996**	**< 0.00001**	**0.937971**	**< 0.00001**
R^2	0.61		0.62		0.99	
$\bar{R}^2$	0.61		0.61		0.99	
Log Likelihood	621.44		631.41		2,051.51	
No. of Observations	1,762		1,762		1,762	

Note: 4NN and 8NN are four and eight nearest neighbors, respectively.

Table 6. Estimated Implicit Prices from the OLS and Spatial Error Models

Variable	OLS	SEM with 4NN	SEM with 8NN	SEM with Inverse Distance
After One Fire	–$32,547	–$30,675	–$29,802	–$30,259
After Two Fires	–$21,274	–$20,072	–$19,340	–$16,161
Cumulative Effect	–$53,821	–$50,747	–$49,142	–$46,419

Table 7. Percentage Difference of Implicit Prices in SEM Model Relative to OLS Model

Variable	SEM with 4NN	SEM with 8NN	SEM with Inverse Distance
After One Fire	–5.75%	–8.43%	–7.03%
After Two Fires	–5.65%	–9.09%	–24.03%

Conclusions

The relatively small difference between our implicit prices from OLS estimates relative to spatially corrected estimates supports the conclusion that using OLS in hedonic models to estimate implicit prices of environmental amenities may give reasonable estimates of these implicit prices even when spatial dependence is present. The spatial error parameter λ is statistically significant in our spatial error models. Thus, from a statistical perspective, we find significant evidence that an SEM is an improvement over OLS. From a purely theoretical standpoint, OLS yields inefficient estimates in our data. However, from a practical standpoint, this difference may not be economically significant because it may not be large enough to meaningfully affect the benefit-cost ratio or policy decision in project evaluation or regulatory impact analyses. For example, only one coefficient estimate using one type of weighting matrix resulted in coefficient estimates with a difference of more than 10% relative to OLS.

We refer to economic significance as a practical application beyond pure statistical significance. As economists, we should be cognizant of the added time spent obtaining spatial data and performing more elaborate spatial analyses. Statistical significance and robustness are vital to a rigorous empirical study. Yet, at times, this rigor may not be achievable because of lack of spatial data and project time limitations. Our study provides evidence that hedonic property studies without statistical corrections for spatial dependence still may be useful for benefit-cost analysis and benefits transfer.

It is important to note, however, that our findings reflect the specific nature of our data. The area of study is a relatively small geographical area. If the neighborhood demographic characteristics we include in our model accurately reflect differences in house prices relative to location, this may reduce the necessity for correcting for spatial effects. One way this issue could be investigated further is to eliminate the demographic characteristics and analyze the significance of the λ parameter.[21] Including the demographics may be implicitly correcting for the spatial dependence.

Currently, no widespread and commonly practiced procedure exists for choosing spatial model specifications. While some studies use the robust tests suggested in Anselin (2005), others use less powerful tests such as Moran's I, simple LM tests, or other less robust procedures. As noted earlier, Bayesian methods can be used to inform both model specification and choice of weights matrices. Further investigation into these methods is an avenue for future research. Not all studies employ the same methods of testing for spatial dependence and spatial specification choice. Consequently, it is possible that some of the studies finding large differences in estimated implicit prices of spatial models relative to OLS did not select the correct spatial specification.

Other avenues for further research include Monte Carlo type experiments to attempt to determine the exact nature and magnitude of spatial dependence required to cause economically significant bias in OLS estimates relative to spatially corrected estimates. In addition, a meta-analysis of hedonic property studies that have both OLS and spatially corrected coefficients would be informative. This study offers insight into the possibility that if geo-coded spatial data are unavailable for a hedonic property model, reasonable estimates may be obtained by using OLS despite the inherent spatial nature

[21] We thank Craig Bond for pointing out this possibility.

of the data. Moreover, older, nonspatial hedonic property models may still provide useful estimates of implicit prices for benefits transfer.

[*Received June 2007; final revision received June 2008.*]

References

Anselin, L. "Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity." *Geographical Analy.* 20,1(1988):1–17.

———. "Under the Hood: Issues in the Specification and Interpretation of Spatial Regression Models." *Agr. Econ.* 27(2002):247–267.

———. "Exploring Spatial Data with GeoDa: A Workbook." 2005. Online. Available at http://www.geoda.uiuc.edu/pdf/geodaworkbook.pdf.

Anselin, L., and A. Bera. "Spatial Dependence in Linear Regression Models." In *Handbook of Applied Economic Statistics*, eds., A. Ullah and D. E. A. Giles, pp. 237–289. New York: Marcel Dekker, Inc., 1998.

Anselin, L., A. Bera, R. Florax, and M. Yoon. "Simple Diagnostic Tests for Spatial Dependence." *Regional Sci. and Urban Econ.* 26(1996):77–104.

Bateman, I., W. Yang, and P. Boxall. "Geographical Information Systems and Spatial Analysis in Resource and Environmental Economics." In *The International Yearbook of Environmental and Resource Economics*, eds., T. Titenberg and H. Folmer, pp. 43–92. North Hampton, MA: Edward Elgar, 2007.

Bell, K. P., and N. E. Bockstael. "Applying the Generalized-Moments Estimation Approach to Spatial Problems Involving Micro-Level Data." *Rev. Econ. and Statis.* 82,1(2000):72–82.

Bell, K. P., and T. J. Dalton. "Spatial Economic Analysis in Data-Rich Environments." *J. Agr. Econ.* 50,3(2007):487–501.

Beron, K. J., J. C. Murdoch, M. A. Thayer, and W. Vijverberg. "An Analysis of the Housing Market Before and After the 1989 Loma Prieta Earthquake." *Land Econ.* 73(1997):101–113.

Bin, O., and S. Polasky. "Effects of Flood Hazards on Property Values: Evidence Before and After Hurricane Floyd." *Land Econ.* 80(2004):490–500.

Boxall, P. C., W. H. Chan, and M. L. McMillan. "The Impact of Oil and Natural Gas Facilities on Rural Residential Property Values: A Spatial Hedonic Analysis." *Resour. and Energy Econ.* 27(2005): 248–269.

Brasington, D. M., and D. Hite. "Demand for Environmental Quality: A Spatial Hedonic Analysis." *J. Regional Sci. and Urban Econ.* 35(2005):57–82.

Chivers, J., and N. Flores. "Market Failure in Information: The National Flood Insurance Program." *Land Econ.* 78(November 2002):515–521.

Cropper, M. L., L. B. Deck, and K. E. McConnell. "On the Choice of Functional Form for Hedonic Price Functions." *Rev. Econ. and Statis.* 70,4(1988):668–675.

Donovan, G., P. Champ, and D. Butry. "The Impact of Wildfire Risk on Housing Price: A Case Study from Colorado Springs." *Land Econ.* 83,2(2007):217–233.

Freeman, A. M. *Measuring Environmental and Resource Values.* Washington, DC: Resources for the Future Press, 1993.

Gayer, T., J. T. Hamilton, and W. K. Viscusi. "Private Values of Risk Tradeoffs at Superfund Sites: Housing Market Evidence on Learning About Risk." *Rev. of Econ. and Statis.* 82,3(2000):439–451.

Holloway, G., D. Lacombe, and J. Lesage. "Spatial Econometric Issues for Bio-Economic and Land-Use Modeling." *J. Agr. Econ.* 58,3(2007):549–588.

Hunt, L. M., P. Boxall, J. Englin, and W. Haider. "Remote Tourism and Forest Management: A Spatial Hedonic Analysis." *Ecological Econ.* 53(2005):101–113.

Kim, C. W., T. T. Phipps, and L. Anselin. "Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Approach." *J. Environ. Econ. and Mgmt.* 45(2003):24–39.

Loomis, J. B. "Do Nearby Forest Fires Cause a Reduction in Residential Property Values?" *J. Forest Econ.* 10(2004):149–157.

Loomis, J. B., and M. Feldman. "Estimating the Benefits of Maintaining Adequate Lake Levels to Homeowners Using the Hedonic Property Method." *Water Resour. Res.* 39,9(2003):1–6.

Palmquist, R. "Hedonic Methods." In *Measuring the Demand for Environmental Quality*, eds., J. Braden and C. Kolstad, pp. 77–119. Amsterdam: Elsevier Science Publishers/North-Holland, 1991.

Pattanayak, S. K., and D. T. Butry. "Spatial Complementarity of Forests and Farms: Accounting for Ecosystem Services." *Amer. J. Agr. Econ.* 87,4(2005):995–1008.

Rosen, S. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *J. Polit. Econ.* 82(1974):34–55.

Taylor, L. "The Hedonic Method." In *A Primer on Non-Market Valuation*, eds., P. Champ, T. Brown, and K. Boyle, pp. 331–394. Dordrecht, The Netherlands: Kluwer Academic Publishers, 2003.